On Assessing the Impact of Transportation Policies on Fuel Consumption and Greenhouse Gas Emissions Using a Household Vehicle Fleet Simulator

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ABSTRACT
The carbon footprint of personal travel is dependent on the composition of the vehicle fleet and the extent to which vehicles of different types are utilized. Transportation model systems have previously not explicitly incorporated the ability to forecast vehicle fleet composition and utilization patterns of households in a region. In the absence of such modeling capability, it is difficult to predict the energy and environmental impacts of alternative policy, market, and technology scenarios in the future. This paper describes the application of a comprehensive vehicle fleet composition and evolution model system that is capable of taking a base year vehicle fleet and evolving it over time in annual time steps through the events of vehicle disposal, replacement, and acquisition. Results of the scenario application exercise documented in this paper demonstrate the efficacy of the model system.

Keywords: vehicle fleet composition modeling, vehicle miles prediction, microsimulation modeling, vehicle and population evolution model application, estimation of energy and greenhouse gas emissions.

INTRODUCTION

Transportation plays a major role in contributing to energy consumption and greenhouse gas emissions in the United States and around the world. In the United States, on-road vehicular travel accounts for nearly 70 percent of all petroleum consumption in the country (USDOE, 2012). Also, travel by light duty vehicles (passenger cars, sport utility vehicles, pickup trucks, and vans and minivans) accounts for nearly two-thirds of the emissions attributable to vehicular travel in the United States (EPA, 2006). Although alternative fuel vehicles are entering the market at a torrid pace and gaining market share, the vast majority of vehicles (93.2 percent) continue to be fossil-fuel powered entities that depend on petroleum and emit greenhouse gas emissions (USDOE, 2012). Policy actions aimed at enhancing the share and use of alternative and clean fuel vehicles, and reducing the carbon footprint of personal travel, can be identified and their potential costs and benefits evaluated only if planning professionals have the ability to forecast the vehicle fleet mix and associated energy and emissions impacts under alternative scenarios.

Over the past several years, there has been considerable progress in the modeling of household vehicle fleet composition and utilization behavior (Bhat and Sen, 2006; Bhat, et al, 2009). These models make it possible to forecast the mix of vehicles that households will own and the extent to which each vehicle in a household fleet will be driven (utilized) under a wide variety of scenarios and system conditions. More recently, a comprehensive vehicle fleet simulation and evolution model system was developed as part of a larger activity-based travel demand model development effort for the Southern California Association of Governments (SCAG). The activity-based travel demand model system, called SimAGENT (Simulator of Activities, Greenhouse emissions, Energy, Networks, and Travel), is capable of simulating the activity-travel patterns of all households and individuals in the Southern California region, a model region that includes a population of about 18 million in the 2008 model base year (Goulias, et al, 2012). Within this comprehensive model system, a household vehicle fleet composition and evolution simulator has been developed and incorporated so that energy consumption and greenhouse gas emissions forecasts can take into account the evolution of the household vehicle fleet mix over time. The vehicle fleet composition and evolution simulator is capable of evolving household fleet mix over time by reflecting and modeling household decisions to acquire, replace, and dispose of vehicles on an annual time scale. The next section provides a brief description of the vehicle fleet mix and evolution simulator and a complete description is available in Paleti, et al (2011).

The objective of this paper is to apply this model system, in conjunction with a population evolution model system, to a few different vehicle policy scenarios and forecast the impacts of the policy actions on vehicle fleet composition, and resultant energy and emissions estimates of the future. The intent of the paper is to test and examine the ability of the model system to provide reasonable estimates of forecasts of vehicle fleet composition that may be used to assess the energy and environmental impacts of alternative policy actions. In the face of recent legislative initiatives in California (such as SB375 and AB32; Clayton, 2009), it is imperative that transportation demand forecasting model systems include vehicle fleet composition and evolution simulator capable of reflecting dynamics in the vehicle fleet mix (and resultant changes in fuel consumption and greenhouse gas emissions) brought about by socio-economic, demographic, technological, built environment, and policy changes.

The remainder of this paper is organized as follows. The next section offers a brief overview of the vehicle fleet simulator. The third section describes the policies considered for evaluation in this paper. Results of the policy simulations are offered in the fourth section. Concluding remarks are offered in the fifth and final section.

SIMULATION MODEL SYSTEM

The activity-based travel demand model system developed for the Southern California Association of Governments (SCAG) is a comprehensive simulator of activity-travel choices of households and individuals in the region (Goulias, et al, 2012). For purposes of this study, there are a few specific modules or components of SimAGENT that have to be invoked so that forecasts of vehicle fleet composition, and energy and emissions, can be obtained. This section presents a brief description of these specific modules.

Vehicle Fleet Simulator

The vehicle fleet simulator (Paleti, et al, 2011) consists of two principal components: (1) The vehicle selection module, and (2) The vehicle evolution module. Each vehicle type alternative in the vehicle selection module is defined as a combination of six vehicle body types (compact car, car, small cross utility vehicle, sport utility vehicle or SUV, van, and pick-up truck), seven fuel types (gasoline, flex fuel, plug-in hybrid, compressed natural gas (or CNG), diesel, hybrid electric, and fully electric), and five age categories (new, 1-2 years, 3-7 years, 8-12 years, and more than 12 years old). Thus, there are a total of 211 vehicle type alternatives including the alternative of no-vehicle. The model system accommodates multiple vehicle ownership and usage dimensions by assuming that vehicle fleet and usage decisions are determined through a series of unobserved (to the analyst) repeated discrete-continuous choice occasions. This framework mimics the dynamics in the vehicle acquisition process by accommodating the impacts of the types of vehicles already owned on the type of vehicle that may be purchased in a subsequent purchase decision. The number of choice occasions in such a "vertical" choice behavior is linked to the number of adults in the household. In particular, since the number of vehicles is almost never greater than the number of adults in the household plus two in the data, the number of choice occasions is set to be equal to the number of adults plus two. At each choice occasion, the household may choose not to purchase a vehicle or to acquire a vehicle of a certain type. In the framework, the decision of the number of vehicles owned by the household is endogenously determined as the sum of those choice occasions when the household chooses to acquire a certain vehicle type. Overall, the vehicle selection module jointly models all base year vehicle fleet characteristics in a unifying framework.

In the vehicle evolution module, the number of choice occasions for evolving the vehicle fleet each year is set equal to the current vehicle fleet plus one. This assumes that households do not add more than one vehicle to their current fleet in any given year after considering replacements; however, the model structure can easily handle any number of additional vehicles (beyond replacements). For any existing vehicle, the household has three options: (1) Keep the vehicle, (2) Dispose the vehicle, and (3) Replace the vehicle (and choose vehicle type and usage level for the replacement vehicle). In addition to evolutionary choice options corresponding to existing vehicles, households may also choose "not to add a vehicle" or "to add a vehicle" (in the latter case, the vehicle type and usage of the added vehicle must be simulated). All of the models in the evolution module are binary logit models that consider temporal dependency across transaction decisions. The vehicle type and usage of all replacement/added vehicles are determined using the vehicle type choice model from the vehicle selection module. The vehicle type choice model includes existing vehicle fleet characteristics and the replaced vehicle characteristics as explanatory variables. This captures dependencies between future vehicle type choices (during evolution) and vehicles already owned and getting replaced.

All of the models in the vehicle fleet simulator are estimated using a unique dataset that includes comprehensive information on vehicle ownership and usage decisions of households, including current fleet composition, potential future fleet composition, and vehicle evolution plans. The vehicle fleet simulator incorporates innovative methodological approaches to address the problem of multiple vehicle holdings and use, as well as to deal with the gamut of vehicle evolution decisions, all in a comprehensive and implementable forecasting framework. Specifically, the simulator encompasses state-of-the-art household vehicle type choice, usage, and evolution models estimated using a special-purpose 2008-2009 vehicle survey data set collected from 6577 households in the State of California by Resource Systems Group, Inc. (RSG) for the California Energy Commission (CEC). The survey has three components: (1) a revealed choice (RC) component, which collected information about current vehicle holdings and usage, (2) a stated intentions (SI) component, which collected information on replacement plans of existing vehicles and vehicle addition plans, and (3) a stated preference (SP) component, which collected information about vehicle choices that respondents would make under hypothetical policy, price, refueling infrastructure, and vehicle attribute scenarios.

Population Evolution Simulator

Any forecasting exercise must recognize explicitly that the population does not remain static over the forecast period. As time progresses, households evolve, persons evolve, and the vehicle fleet composition and utilization patterns evolve. The vehicle fleet composition and utilization simulator includes an evolution module capable of transitioning vehicle fleet mix over time as households acquire, dispose, and replace vehicles. The models embedded in the vehicle fleet simulator are sensitive to a host of socio-economic and demographic variables, built environment variables, and network accessibility measures. As such, it is important – in the context of any forecasting exercise – to evolve the population over the forecast period so that vehicle fleet choices are simulated in a way that reflects the dynamics of socio-economic and demographic characteristics of the population.

The population evolution model system used in this study is based on the CEMSELTS (Comprehensive Econometric Microsimulator of Socioeconomic, Land use, and Transportation Systems) model system which is capable of simulating and evolving a population over time (Pendyala, et al, 2012; Eluru, et al, 2008). The socio-economic modeling system is a comprehensive simulator of the lifecycle processes that households and individuals experience over time. The model system embeds models that cover the following lifecycle processes:

- Emigration and immigration (household migration)
- Aging and mortality (death)
- Fertility (birth)
- Education level and attainment
- Student status
- Labor force participation
- Marriage
- Household dissolution (separation and divorce)
- Child birth
- Child leaving home

- Driver license holding and attainment
- Transit pass holding and attainment
- Residence location
- Work location
- School location
- Income model

The evolution model system embeds a series of models that are interconnected in recognition of the considerable inter-dependency across lifecycle events. Within the scope of this paper, it is impossible to provide a detailed explanation of the various model components. The model components take the form of simple rate based models or logit choice models depending on the availability of data. Data sets used to develop and calibrate the model system include census data sets, National Center for Health Statistics data, data available from state and county agencies, Panel Survey of Income Dynamics, and National Survey of Family Growth. A complete description of the population evolution model system, the model component specifications, and the data sets used to inform the model system is provided elsewhere (Eluru, et al, 2008).

Vehicle Fleet Prediction

The forecasting exercise conducted in this paper is performed using the sample of 6577 households in the California Energy Commission (CEC) survey. This sample has been found to be reasonably representative of the population in the State of California (Paleti, et al, 2011) and is therefore a suitable sample for applying the evolution model system. The evolution process starts off with the vehicle holdings observed in the data for the base year (2008). For each vehicle in the base year, the model predicts whether the household decides to keep, scrap, or replace the vehicle starting with the oldest vehicle in the vehicle fleet. If there is a scrap decision, the corresponding vehicle is removed from the fleet and the existing vehicle fleet characteristics are updated. Similarly, if there is/are replacement decision(s), then the corresponding vehicle(s) from the vehicle fleet is/are removed and the vehicle selection module is invoked to determine the characteristics of the new vehicle(s) that replaces (replace) the existing vehicle(s). After determining the transaction decisions associated with existing vehicles in the fleet, the household decision to purchase a new vehicle is simulated. If there is an "add vehicle" decision, then the vehicle selection module is invoked to determine the characteristics of the new vehicle.

For any new household created during the population evolution process, the synthetic choice occasions for each newly created household are constructed based on the number of adults in the household. Then, the vehicle selection module is applied to determine the vehicle type (body type, vintage and fuel type of the vehicle) and the associated annual mileage at each of the synthetic choice occasions, updating the vehicle fleet characteristics after each synthetic choice occasion. This process generates the vehicle fleet characteristics for all new households.

This evolution procedure is executed on an annual basis/cycle until the forecast year is reached. During this process, the population evolution model system is deployed to evolve the population over time. Based on the new socio-economic and demographic profile of households and individuals, the vehicle evolution model predicts the vehicular fleet mix in each year of the simulation. This annual evolutionary process reflects the dynamics of the person population and vehicle population and provides rich information useful to understanding changes in regional characteristics over time. The land use, built environment, and network accessibility measures that influence population evolution (residential and work locations, for example) and vehicle evolution are treated as exogenous to the forecasting exercise undertaken in this study. In reality, however, it is plausible to expect built environment and network accessibility measures to change in response to changes in vehicular technology and household location choices; thus such built environment and network accessibility measures are, in reality, endogenous to the model system. However, the application of the population and vehicle evolution model systems within this study required the study team to assume that such data is exogenous to the evolution model systems.

For the analysis of the policy scenarios, the random seeds used in the microsimulation process for each household and for each vehicle choice decision occasion over the course of the forecasting period are held fixed at the base case values to ensure that any changes in the vehicle fleet characteristics and associated mileages are attributable to the policy under consideration.

Fuel Consumption and Greenhouse Gas Emissions Calculations

The vehicle fleet composition and evolution simulator predicts annual vehicle usage along with the vehicle type for each vehicle in a household. This enables the estimation of the total annual fuel consumption by dividing the annual mileage for each vehicle in the fleet with a corresponding fuel economy value (in miles per gallon) based on the vehicle type. The average fuel economy value across all makes/models within each vehicle type (as defined by a combination of body type, vintage, and fuel type) is used as the fuel economy estimate for any particular vehicle type. For all vehicle types until model year 2012, fuel economy data provided by the US Department of Energy is used; this data is freely available for download at http://www.fueleconomy.gov/feg/download.shtml. For all model years beyond 2012, it is assumed that fuel economy will continue to improve, especially in light of federal legislative actions mandating higher fuel economy standards in future years. It is therefore assumed that new model years will come with an annual fuel economy increase of three percent. For example, if a new Gasoline car provides 35 mpg in 2012, then the same car would provide a mileage of 35x1.03 = 36.05 mpg in 2013.

In addition, the study accounts for the proposed new corporate average fuel economy (CAFE) standards for all light duty vehicles of model years 2017 to 2025. Specifically, the new standards require all passenger cars (including sub-compacts to large sedans and station wagons, crossover utility vehicles, SUVs, and minivans) to have a minimum fuel economy of 37.8 miles per gallon (mpg) in model year 2012 and 56.0 mpg in model year 2025 and all light trucks to have a minimum fuel economy of 34.1 mpg in model year 2012 and 49.6 mpg in model year 2025 (NHTSA, 2012). So, all new model years starting 2017 are set to meet these new CAFE standards in case their mileage computed using a three percent annual increase in fuel economy values as described earlier comes out to be lower than the CAFE standard.

A series of assumptions and calculations are made to compute energy consumption and tailpipe emissions for different vehicle types. The study team had to make reasonable assumptions regarding the entry of new vehicles into the market. For example, there are currently no all-electric sport utility vehicles and minivans in the market. It is assumed that such vehicles will become available starting in the model year 2015. The following is a list of assumptions and procedures used to facilitate the computations:

- All costs associated with vehicle usage including vehicle purchase price and vehicle maintenance cost are expected to increase by three percent every year.

- For hybrid-electric vehicles and plug-in hybrids, it is assumed that the liquid fuel (which produces GHG emissions) used in the vehicles is gasoline (and not any other fuel such as diesel or flex fuel). For example, if the fuel economy value of a hybrid-electric vehicle is estimated to be 90 miles per gallon, then it is assumed that the vehicle provides a mileage of 90 miles per gallon of gasoline.
- The fuel economy value estimates of compressed natural gas (CNG) and fully electric vehicles represent the miles per gallon of gasoline equivalent (MPGe) values.
- For CNG vehicles, a Gasoline Gallon Equivalent (GGE) factor of 0.51 cubic feet (at 3600 psi, which is the pressure in most CNG cylinders) is used to convert the gallons of gasoline to equivalent volume of CNG with the same energy content.
- All fully electric vehicles emit zero greenhouse gas (GHG) emissions and thus are not considered in the GHG emissions calculation[1].

At the end of this step, the total fuel consumption by gasoline, diesel, flex fuel, and CNG is obtained. Since the liquid fuel in hybrid-electric and plug-in electric vehicles is assumed to be gasoline, they do not appear separately in the list of fuel types in this study.

The associated CO_2 emissions are estimated based on the following equation that EPA uses for all emissions inventory calculations:

$$\begin{aligned}\mathrm{CO_2\ Emissions/Gallon} &= \mathrm{Carbon\ Content\ of\ Fuel\ x}\left(\frac{\mathrm{Molecular\ Weight\ of\ CO_2}}{\mathrm{Molecular\ Weight\ of\ Carbon}}\right)\mathrm{x\ Oxidation\ Factor}\\ &= \mathrm{Carbon\ Content\ of\ Fuel\ x}\left(\frac{44}{12}\right)\mathrm{x}\ 0.99\end{aligned}$$

The following steps and assumptions are embedded in the greenhouse gas emissions calculation procedure:

- The oxidation factor in the equation accounts for the fact that some percentage of carbon remains un-oxidized. EPA suggests using an oxidation factor of 0.99. Also, EPA uses 2,421 and 2,778 grams as the carbon content in gasoline and diesel vehicles (EPA, 2005).
- It is assumed that all flex fuel vehicles use E85 blend which contains 85 percent ethanol and 15 percent gasoline. Thus, the carbon content of flex fuel is obtained as 2,421x0.15 = 363.15.
- The CO_2 emissions from CNG vehicles are computed using a carbon content value of 490 grams of carbon per cubic meter of CNG. This value is obtained from the Bio-energy Feedstock Information Network (BFIN) website (BFIN, 2012).
- All of the $non-CO_2$ GHG emissions including N_2O, CH_4, and HFC (hydrofluorocarbons) usually constitute 5% of total GHG emissions; so the total CO_2 emissions is multiplied by a factor of $\left(\frac{100}{95}\right)$ to obtain the total GHG emissions (EPA, 2005).

[1] In the current study, we consider only the tailpipe emissions that occur due to vehicle usage but not life-cycle emissions which include production and distribution emissions associated with the fuel.

POLICIES CONSIDERED

The study involved exercising and testing the model system for a variety of policy, market-based, and technological scenarios. In the interest of brevity, and to illustrate the types of sensitivity that the model is capable of reflecting, this paper offers a detailed description of results obtained when the model system was employed to analyze the impacts of three distinct types of policies:

1) Incentive-based policy: Free HOV lane access for all non-gasoline vehicles (CNG, hybrid-electric, plug-in hybrid, and fully electric)
2) Future market scenario: Price of gasoline doubles (in real dollars)
3) Technology-based scenario: Driving range of CNG vehicles and fully electric vehicles will be greater than 200 miles

In order to illustrate the ability of the model to reflect changes brought about by a combination of scenarios, the impacts of a combination of the future market scenario and technology-based scenario are also considered and documented in this paper.

In the baseline scenario against which all policy scenarios are compared, it is assumed that new vehicle mileage values, vehicle purchase prices, fuel costs, and maintenance costs increase by three percent every year. New vehicle mileage values are adjusted if necessary to match CAFE standards set by federal policy (as mentioned earlier). Across all scenarios, it is assumed that the timeline when vehicles of different fuel types become available is exactly the same. This paper documents the impact of the policy and market scenarios on the total number and share of vehicles owned by households, consumption levels of different fuels, and the associated GHG emissions.

RESULTS OF EVOLUTIONARY MODEL SYSTEM APPLICATION

The model system was applied to forecast the person population and the vehicle population, and associated fuel consumption and GHG emissions, to the years 2020 and 2030. The results of the effort are described in this section.

Population Evolution Model

The population evolution model was applied to the baseline survey sample of 6577 households and all of the persons residing in the respondent households. Treating 2008 as the base year and assuming the 6577 households constitutes a base year population, the population size and age distribution forecast by the population evolution model system for horizon years 2020 and 2030 were compared against established forecasts furnished by the California Department of Finance (DOF, 2012) and Pitkin and Myers (2012). As it is not appropriate to compare actual numbers, the population growth and the age distribution of the population were compared for the horizon years.

In general, it is found that the population evolution model is able to replicate established forecasts quite well. The population evolution model used in this study grew the population (of 6577 households) by 9.41 percent to the year 2020; the corresponding population growth increases predicted by California Department of Finance and Pitkin and Myers (2012) are 9.39 and 9.35 percent respectively. By the year 2030, the study forecast a population growth of 18.53 percent. This is slightly lower than, but still very much in line with, the established forecasts of 19.46 percent and 19.90 percent growth predicted by the California Department of Finance and Pitkin and Myers (2012) respectively.

An examination of the age distribution of the future year population predicted by the population evolution model system suggests that the model system tends to age the population more than that implied by the established forecasts. The age distribution of the base year population (i.e., the respondent sample of the survey) is already skewed in favor of older age groups when compared with the true population distribution provided by the California Department of Finance and Pitkin and Myers (2012). The model system then appears to age the population further at a rate that is faster than that implied by the two established benchmark forecasts. In the year 2020, for example, the percent of individuals 65 and above is predicted to be 23 percent in the study (increased from 14.8 percent in the base year); the corresponding percent is 15 percent in the California Department of Finance and Pitkin and Myers (2012) forecast (increased from 11.5 percent in the base year). Similar differences are seen in the 2030 forecast as well. In the year 2030, the study predicts that 28.5 percent of the population will be 65 or above; the corresponding forecast provided by the California Department of Finance and Pitkin and Myers (2012) is just under 19 percent. It appears that the model is aging the population, but may not be adequately reflecting international immigration patterns which balance and moderate the aging of the population. The differences in age distribution have implications; as vehicle fleet composition is sensitive to socio-economic and demographic characteristics, the aging of the population will impact vehicle fleet forecasts produced in this study. The results of the model application effort should be interpreted with this cautionary note in mind. Nevertheless, the exercise is useful in demonstrating the application of the model for analyzing alternative scenarios.

Vehicle Fleet Forecasts

The vehicle fleet forecasts that result from the application of the vehicle evolution model system are presented in Table 1. The base year values are those for 2008, the year of the California Energy Commission survey. Assuming a standard progression as per the assumptions outlined earlier in this paper, baseline estimates of various attributes may be obtained for the forecast years of 2020 and 2030. In the base year of 2008, it is found that the 6577 households own 13016 vehicles. Under baseline growth conditions, the number of vehicles increases to 15548 and 16697 respectively in 2020 and 2030. Although the number of vehicles increases, the vehicle ownership per household actually decreases, presumably because the increase in the number of households is greater than the increase in the number of vehicles. It is likely that the aging of the population (predicted by the population evolution model) contributes to this phenomenon; households with older individuals are likely to be smaller in size and have fewer cars. Moreover, individuals in these age groups may have ceased driving thus reducing car ownership and driving levels. The results are consistent with the population evolution predicted by the socio-economic model system.

The vehicle fleet forecasts under baseline growth conditions suggest that the share of pick-up trucks will drop, and then increase again in the year 2030. This is likely an artifact of the assumptions about technology availability that are inherent to the study. The study assumes that fuel-efficient options among pick-up trucks become available starting in the year 2020. With respect to fuel type, it is found that – even in the baseline growth conditions – the share of gasoline vehicles drops dramatically. The share of gasoline vehicles drops to less than one-half of the value in the base year. As the baseline growth scenario incorporates a number of assumptions regarding the availability of fuel efficient and alternative fuel vehicles in horizon years, it is not surprising to see the vehicle fleet composition shift considerably towards alternative fuel vehicles in the future. The share of flex fuel vehicles increases dramatically, along with that of hybrid vehicles (both plug-in hybrid and hybrid electric) and diesel vehicles. Based on the vehicle fleet evolution model predictions in this study, the future is likely to be characterized by a heterogeneous mix of vehicle types on the nation's roadways. As households shed gasoline cars and acquire newer fuel efficient and alternative fuel vehicles, the age distribution of the fleet undergoes considerable change as well. The fleet becomes considerably younger with nearly 30 percent of the vehicles new in the years 2020 and 2030, compared to a much smaller 5.82 percent of vehicles classified as new in the base year of 2008.

If free HOV lane access is granted to all non-gasoline vehicles (CNG, hybrid-electric, plug-in hybrid, and fully electric), then the total number of vehicles in the population increases slightly. It appears that there may be greater acquisition of vehicles (particularly non-gasoline vehicles) to take advantage of the free HOV lane access afforded these vehicles. There is no appreciable change in the body type distribution between the baseline scenario forecasts and the HOV lane access scenario forecasts. In general, with inherent assumptions that technology options become available in the future in both scenarios, it is not surprising that both scenarios produce similar body type distributions for the fleet forecast. The age distribution is likewise rather similar between the baseline forecast scenario and the free HOV lane access scenario. The difference, as expected, is seen primarily in the fuel type distribution. With free HOV lane access for alternative fuel vehicles, the share of gasoline cars falls further to just about one-third of all vehicles in the year 2030. The share of flex fuel vehicles falls as well (because the HOV lane access is not granted to these vehicles. The share of all other vehicle fuel types increases with rather large increases in plug-in hybrid and hybrid electric vehicle shares. The share of diesel vehicles drops relative to the baseline scenario as consumers shift to the various types of electric vehicles.

In the case of the scenario where gas cost doubles, it is found that vehicle ownership levels decrease. The total number of vehicles increases more modestly from the base year (relative to the baseline forecast scenario) and the average number of vehicles per household decreases considerably, reaching a value of 1.62 in 2030 (relative to 1.98 in the base year of 2008). When gas cost doubles, there is shorter term shift towards smaller vehicle body types. The share of compact cars increases (relative to the base year of 2008) and is higher than that forecast in the baseline growth scenario. Although the share of cars decreases, the share of small cross utility vehicles increases considerably when compared with the 2008 share. The share of larger vehicles such as sport utility vehicles and pick-up trucks decreases. As the study assumes the availability of fuel efficient versions of the large vehicles starting in 2020, the share of large vehicle body types increases once again between 2020 and 2030. An examination of the age distribution shows that vehicles become considerably younger in the short term, as households turnover their fleet more rapidly in response to a doubling of gas cost. However, in the long term (to 2030), the share of older vehicles increases (relative to 2020) while the share of vehicles in the 1-7 year age range decreases.

The doubling of gas cost is predicted to have an appreciable impact on fuel type distribution in the fleet. However, the model system predicts that the shift away from gasoline cars is smaller in this scenario than the free HOV lane access scenario. In the doubling of gas cost scenario, the share of gasoline vehicles stays at about 40 percent; in the free HOV lane access scenario, the share of gasoline vehicles dropped to about 33 percent. While the share of pure electric vehicles goes up across the two scenarios, the share of hybrid and plug-in electric hybrid vehicles is lower in the gas cost doubling scenario than the free HOV lane access scenario. These findings are consistent with the notion that traveler choices and behavior are largely insensitive to changes in fuel price; travel demand is generally inelastic with respect to gas prices (Goodwin, et al, 2004; Graham and Glaister, 2004).

The scenario where driving range of CNG and fully-electric vehicles is dramatically increased to over 200 miles offers forecasts that are quite consistent with expectations. Vehicle ownership levels are slightly higher than in the baseline growth scenario, presumably because households acquire the new high-range alternative fuel vehicles. In the body type distribution, it is found that the share of vans increases considerably relative to the other scenarios. It is likely that households (which have aged over time) would like to acquire comfortable and family-friendly vans that are easy to drive when there is no range anxiety associated with the electric and CNG versions of these vehicles. The age distribution shows that households are inclined to acquire new electric vehicles with no range issues; the percent of new vehicles in the fleet is about 40 percent in the forecast years under the increased driving range scenario. The most dramatic shift can be seen, as expected, in the fuel type distribution. The share of fully electric vehicles increases dramatically to constitute about one-fourth of the fleet in the scenario forecast years. The share of gasoline vehicles drops to about one-third of all vehicles.

As expected the combination scenario shows a more dramatic impact across the dimensions of interest. With a doubling of gas cost coupled with a dramatic increase in driving range, the shares of CNG and fully electric vehicles increase even further relative to all other scenarios. The shares of gasoline, flex fuel, and other types of electric vehicles drop even further. Overall, it can be seen that the vehicle evolution model system, coupled with a population evolution model system, is able to provide vehicle fleet forecasts that are intuitive and insightful in response to changes in policy, market, and technology availability conditions.

Fuel Consumption and Emissions Forecasts

Table 2 presents the fuel consumption and greenhouse gas emissions forecasts for the alternative scenarios considered in this study. In the baseline scenario, it is found that average annual household mileage decreases over the long term, but average annual vehicle mileage increases. With the aging of the population (as predicted by the population evolution model system), it is likely that household sizes are reduced and presence of children is less relative to the base year. As a result, household mileage reduces; on the other hand, the increased discretionary time that older people have, combined with the increased share of alternative and clean fuel vehicles, is likely to result in an increase in per vehicle mileage. As households are forecast to own fewer vehicles in the future, the vehicles that they do have end up being driven more on a per-vehicle basis. In the baseline scenario forecast, it is found that gasoline consumption decreases considerably while consumption of other fuels increases. This is consistent with the earlier findings reported in Table 1 where the share of gasoline vehicles drops dramatically from the base year to the forecast years. As a consequence, the simulation results show that greenhouse gas emissions (last row of Table 2) decrease substantially in the forecast years (under the baseline scenario).

With free HOV lane access, it should be recalled that households shifted to electric vehicles of all types and decreased share of gasoline, flex fuel, and diesel vehicles. This shift in fleet mix is reflected in the results for this scenario in Table 2. While there is no appreciable change in mileage values relative to the baseline scenario, it is found that the total gasoline consumption is slightly higher in the free HOV lane access scenario relative the baseline scenario. This is likely because of the large increase in the share of plug-in hybrid and hybrid-electric vehicles that was forecast by the vehicle fleet forecasting model system. The energy consumption of these vehicles was converted into equivalent gasoline consumption and their greater presence in the fleet mix contributes to greater gasoline consumption. On the other hand, there is a decrease in flex fuel consumption and diesel consumption relative to the baseline scenario. The total emissions show a considerable drop, presumably because the hybrid electric and plug-in hybrid electric vehicles emit less greenhouse gas emissions than diesel vehicles and flex fuel vehicles (both of which exhibited larger shares in the baseline scenario case).

A doubling of gas cost results in a decrease in the annual average household mileage, both relative to the base year and relative to the baseline forecast. It appears that the doubling of gas cost results in a lower utilization (miles driven) of vehicles and the vehicle fleet composition and utilization model system is able to reflect this phenomenon. On a per-vehicle basis, however, it is found that average annual vehicle mileage is higher in the future under the doubling of gas cost relative to the base year. With fewer vehicles owned by households relative to the base year, it is not unexpected for the mileage accrued on a per-vehicle basis to be larger relative to the base year. However, this value is smaller relative to the baseline scenario forecast suggesting that the doubling of gas cost has a dampening effect relative to a baseline growth scenario. As expected, doubling of gas cost brings about a substantial decrease in total gasoline consumption relative to the base year, and relative to the baseline forecast. Only the consumption of CNG increases relative to the baseline scenario as the share of these vehicles in the fleet increases and the price of CNG remains unchanged. The reduced vehicle miles of travel coupled with a shift in vehicle fleet mix (there is an increase in CNG and fully-electric vehicle share in this scenario) contributes to a substantial drop in total greenhouse gas emissions in this scenario. The drop in greenhouse gas emissions is considerably larger in this scenario than in the free HOV lane access scenario. This is consistent with expectations; the free HOV lane access is an incentive to use alternative fuel vehicles, but not reduce vehicle utilization. The doubling of gas cost is an incentive to both use alternative fuel vehicles and reduce vehicle utilization (wherever a gasoline vehicle is involved). This combination contributes to the rather large drop in emissions seen in the last row of Table 2 for this scenario.

The increase in driving range for CNG and fully-electric vehicles is associated with an increase in average annual household mileage and a rather stable per-vehicle average annual mileage relative to the baseline scenario. With the elimination of range anxiety, travelers are now able to drive vehicles longer distances and this contributes to the increased mileage relative to the baseline scenario. As the vehicle fleet mix shifts considerably with a greater share of CNG and fully-electric vehicles, the gasoline consumption drops substantially in this scenario. Compared to the baseline scenario, gasoline consumption is lower by about 35 percent (the corresponding percent reduction in the doubling of gas cost scenario is 13.4 percent in 2030). Similarly, the consumption of flex fuel drops substantially, while the consumption of CNG fuel increases relative to the baseline scenario. When compared with the gas cost doubling scenario and the free HOV lane access scenario, the increased driving range scenario offers the largest decreases in greenhouse gas emissions.

As expected a combination scenario offers even greater benefits with the reductions in gasoline consumption and greenhouse gas emissions virtually equal to the sum of the reductions seen when the policy actions were implemented in isolation. The combination scenario involves a doubling of gas cost and an increase in the driving range for CNG and fully-electric vehicles. In the combination scenario, it is seen that mileage is fairly stable; the doubling of gas cost is compensated by the increase in driving range and the combination scenario results in mileage values rather similar to those seen in the baseline forecast scenario. However, reductions in gasoline consumption and greenhouse gas emissions amount to nearly 50 percent in the year 2030 when compared with the baseline scenario.

Overall, it can be seen that the vehicle fleet composition, utilization, and evolution simulator exhibits the ability to forecast vehicle fleet mix and consequent shifts in fuel consumption and greenhouse gas emissions under a wide range of scenarios. The model offers results that are behaviorally intuitive and consistent with the changes in system conditions imposed in the scenarios.

CONCLUSIONS

This paper describes the application of a comprehensive vehicle fleet composition and evolution model system that is capable of evolving a base year vehicle fleet in an annual time step. The model system operates in a microsimulation framework at the level of the household and is therefore ideally suited for integration in activity-based travel demand modeling approaches. The vehicle fleet simulator is applied to a host of scenarios to investigate the ability of the model system to provide forecasts of vehicle fleet composition, annual fuel consumption, and greenhouse gas emissions under alternative scenarios. The population and vehicle fleet are evolved in annual time steps to the years 2020 and 2030 (starting with a base year of 2008) for the 6557 households in the survey sample. In addition to a baseline forecast scenario, the application considers three policy and market scenarios, including free HOV lane access for alternative fuel vehicles, a doubling of gas cost, and an increase in driving range for CNG and fully-electric vehicles to greater than 200 miles. A fourth scenario is also considered – that of the combination of the doubling of gas cost and increase in driving range. The model is found to be offer behaviorally plausible forecasts of vehicle fleet mix, greenhouse gas emissions, and fuel consumption under the alternative scenarios.

Based on the findings from the study, it appears that future technological innovations (increase of driving range, for example) and pricing levels (doubling of gas cost) will have greater impacts on vehicle fleet composition, utilization, energy consumption, and greenhouse gas emissions than more incentive based approaches such as free HOV lane access for alternative fuel vehicles. Given that under some policy scenarios, the share of electric vehicles can increase substantially, it is important to undertake more comprehensive analysis of the additional burden that this shift would put on the electricity infrastructure of a region. Also, innovative strategies to meet the demand must be explored to facilitate this impending transition towards electric vehicles (Anderson, et al, 2009). Also, this study and the model system it utilizes focus only on the emissions associated with vehicle operation. However, although fully electric vehicles produce zero emissions while in operation, there are some emissions associated with the car manufacturing and electricity generation processes. A more comprehensive well-to-wheel analysis is needed to understand the overall impact of these policies on the environment (Thomas, 2012).

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Table 1. Vehicle Fleet Composition in 2020 and 2030

	Base Year	Baseline Forecast		Scenario: HOV Lane Access		Scenario: Gas Cost Doubles		Scenario: Increased Driving Range		Scenario: Combination: Gas Cost Doubles + Increased Driving Range	
	2008	**2020**	**2030**	**2020**	**2030**	**2020**	**2030**	**2020**	**2030**	**2020**	**2030**
Total Number of vehicles	13016	15548	16697	15609	16908	14832	15823	16091	17422	15536	16843
Average Number of Vehicles per Household	1.98	1.84	1.71	1.84	1.73	1.75	1.62	1.90	1.78	1.83	1.72
Body Type											
Compact Car	22.24	23.65	21.56	23.72	20.59	24.74	22.29	20.23	17.55	21.92	17.87
Car	28.15	26.38	24.53	27.60	26.10	26.15	25.47	23.11	21.91	24.85	23.84
Small cross utility veh.	5.57	8.67	6.97	7.34	5.50	9.20	7.63	8.69	7.15	10.65	7.80
Sports utility vehicle	20.02	19.93	19.88	20.43	19.62	19.34	18.42	19.95	17.98	15.95	14.90
Van	6.84	7.18	8.06	6.51	8.11	7.25	8.30	17.76	22.12	17.68	23.94
Pick-up truck	17.18	14.20	19.00	14.40	20.07	13.32	17.90	10.25	13.29	8.95	11.65
Fuel Type											
Gasoline	96.45	45.07	40.65	36.45	32.87	42.17	39.13	36.65	33.33	29.06	27.22
Flex Fuel	0.26	14.45	12.85	10.99	9.34	14.93	12.99	8.35	6.84	6.67	5.25
Plug-in Hybrid	0.02	9.48	12.01	14.01	17.88	9.57	12.07	5.23	6.98	4.06	5.19
CNG	0.07	0.49	0.43	0.67	0.75	0.80	0.86	3.36	3.74	5.41	5.25
Diesel	2.23	12.72	15.18	10.54	11.46	12.20	13.49	15.18	15.04	11.88	11.98
Hybrid Electric	0.93	15.08	15.22	22.79	22.16	14.49	14.78	8.17	7.00	6.23	5.98
Fully Electric	0.04	2.71	3.66	4.56	5.54	5.85	6.68	23.06	27.07	36.69	39.13
Vintage											
New	5.82	30.34	29.73	29.62	28.85	32.65	33.91	40.09	38.15	39.04	36.13
1-2 years	14.98	19.55	15.55	20.26	15.61	19.07	14.73	16.71	12.40	17.26	12.68
3-7 years	35.69	21.57	18.48	21.33	18.38	20.40	16.73	19.05	15.62	19.50	15.12
8-12 years	23.89	16.07	20.08	15.81	19.49	15.66	18.43	13.54	18.04	13.99	18.51
More than 12 years old	19.63	12.47	16.16	12.98	17.68	12.23	16.20	10.60	15.78	10.21	17.56

Table 2. Vehicle Mileage, Fuel Consumption, and Emissions in 2020 and 2030

	2008	Baseline		Scenario: HOV Lane Access		Scenario: Gas Cost Doubles		Scenario: Increased Driving Range		Scenario: Combination: Gas Cost Doubles + Increased Driving Range	
		2020	2030	2020	2020	2030	2030	2020	2030	2020	2030
Average Annual Household Mileage (miles)	25368.10	26666.83	24244.68	26664.96	24283.39	25219.69	22844.96	27925.92	25292.33	26775.42	24392.05
% change from 2008	--	5.12	-4.43	5.11	-4.28	-0.59	-9.95	10.08	-0.30	5.55	-3.85
% diff. from Baseline	--	--	--	-0.01	0.16	-5.43	-5.77	4.72	4.32	0.41	0.61
Average Annual Vehicle Mileage (miles)	12818.53	14530.57	14205.29	14472.78	14050.42	14405.42	14124.52	14703.15	14202.44	14601.02	14167.75
% change from 2008	--	13.36	10.82	12.91	9.61	12.38	10.19	14.70	10.80	13.91	10.53
% diff. from Baseline	--	--	--	-0.40	-1.09	-0.86	-0.57	1.19	-0.02	0.48	-0.26
Total Mileage (miles)/10^6	166.85	225.92	237.19	225.91	237.56	213.66	223.49	236.59	247.43	226.84	238.63
% change from 2008	--	35.41	42.16	35.40	42.39	28.06	33.95	41.80	48.30	35.96	43.02
% diff. from Baseline	--	--	--	-0.01	0.16	-5.43	-5.77	4.72	4.32	0.41	0.61
Total Fuel Consumption: Gasoline (in gallons)/10^6	7.78	5.31	4.78	5.47	5.02	4.69	4.14	3.72	3.10	2.70	2.40
% change from 2008	--	-31.66	-38.59	-29.60	-35.41	-39.65	-46.81	-52.14	-60.14	-65.30	-69.10
% diff. from Baseline	--	--	--	3.01	5.17	-11.70	-13.39	-29.97	-35.10	-49.23	-49.68
Total Fuel Consumption: Flex Fuel (in gallons)/10^6	0.02	1.16	0.95	0.87	0.68	1.08	0.90	0.68	0.53	0.53	0.36
% change from 2008	--	5436.45	4433.10	4086.68	3167.29	5070.05	4196.27	3143.73	2425.32	2430.45	1623.77
% diff. from Baseline	--	--	--	-24.38	-27.92	-6.62	-5.22	-41.41	-44.29	-54.29	-61.97
Total Fuel Consumption: CNG (in gge)/10^6	0.01	0.04	0.03	0.06	0.06	0.06	0.06	0.30	0.32	0.45	0.42
% change from 2008	--	578.31	455.62	909.49	974.46	884.40	909.22	5113.54	5442.60	7692.70	7124.25
% diff. from Baseline	--	--	--	48.82	93.38	45.12	81.64	668.60	897.55	1048.83	1200.21
Total Fuel Consumption: Diesel (in gallons)/10^6	0.19	1.02	1.10	0.85	0.86	0.89	0.93	1.07	0.93	0.77	0.69
% change from 2008	--	434.52	475.68	344.82	350.67	368.29	386.90	459.25	386.77	305.77	259.34
% diff. from Baseline	--	--	--	-16.78	-21.72	-12.39	-15.42	4.63	-15.45	-24.09	-37.58
Total Emissions (grams)/10^6	73994.89	60444.94	55763.35	59156.22	54513.76	53329.03	48129.17	46047.04	38478.69	33481.03	29448.73
% change from 2008	--	-18.31	-24.64	-20.05	-26.33	-27.93	-34.96	-37.77	-48.00	-54.75	-60.20
% diff. from Baseline	--	--	--	-2.13	-2.24	-11.77	-13.69	-23.82	-31.00	-44.61	-47.19